ADVANCED NEURAL NETWORKING AND CLASSIFICATION TECHNIQUES FOR HUMAN BRAIN TISSUES DIAGNOSES: SEGMENTING HEALTHY, CANCER AFFECTED AND EDEMA BRAIN TISSUES

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DEDICATION.

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ABSTRACT

The brain tumors, are the most common and aggressive disease, leading to a very short life expectancy in their highest grade. Thus, treatment planning is a key stage to improve the quality of life of patients. Generally, various image techniques such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI)and ultrasound image are used to evaluate the tumor in a brain, lung, liver, breast, prostate and etc. Especially, in this work MRI images are used to diagnose tumor in the brain. However, the huge amount of data generated by MRI scan thwarts manual classification of tumor vs non-tumor in a particular time. But it having some limitation accurate quantitative measurements is provided for limited number of images. Hence trusted and automatic classification scheme are essential to prevent the death rate of human. The automatic brain tumor classification is very challenging task in large spatial and structural variability of surrounding region of brain tumor. In this work, automatic brain tumor detection is proposed segment the Region Proposal Network (RPN) by Faster R-CNN algorithm. Here, the concept of transfer learning is used during training. The proposed system helps to predict the correct type of tumor with better accuracy about 99%. and classifying by using Convolutional Neural Networks (CNN). The deeper architecture design is performed by using small kernels. Experimental results show that the CNN archives rate of 98% accuracy with low complexity and compared with the all other state of arts methods.

ABSTRAK

Tumor otak, adalah penyakit yang paling biasa dan agresif, yang membawa kepada jangka hayat yang sangat pendek dalam gred tertinggi mereka. Oleh itu, perancangan rawatan adalah peringkat penting untuk meningkatkan kualiti hidup pesakit. Secara umumnya, pelbagai teknik imej seperti *Computed Tomography* (CT), *Magnetic Resonance Imaging* (MRI) dan imej ultrasound digunakan untuk menilai tumor dalam otak, paru-paru, hati, payudara, prostat, dan sebagainya. Dalam karya ini, imej MRI digunakan untuk mendiagnosis tumor di dalam otak. Bagaimanapun, sejumlah besar data yang dihasilkan oleh imbasan MRI menggagalkan pengkelasan manual tumor ataupun bukan tumor pada masa tertentu. Oleh itu, ia mempunyai beberapa pengukuran kuantitatif yang tepat disediakan untuk bilangan imej yang terhad. Maka, skim klasifikasi yang dipercayai dan automatik adalah penting untuk mengawal kadar kematian manusia. Klasifikasi tumor otak secara automatik adalah tugas yang sangat mencabar dalam variasi spatial dan struktur yang besar di kawasan sekitar tumor otak. Dalam kerja ini, pengesanan tumor otak automatik dicadangkan, iaitu segmen Rangkaian Cadangan Wilayah (RPN) oleh algoritma R-CNN Pantas. Di sini, konsep pemindahan pembelajaran digunakan semasa latihan. Sistem yang dicadangkan membantu untuk meramalkan jenis tumor yang betul dengan ketepatan yang lebih baik sekitar 99%, dan mengelaskan menggunakan Rangkaian Neural Convolutional (CNN). Reka bentuk seni bina yang lebih dalam dilakukan menggunakan kernel yang kecil. Keputusan eksperimen menunjukkan bahawa kadar arkib CNN mempunyai ketepatan 98% dengan kadar kerumitan yang rendah, berbanding dengan semua kaedah-kaedah yang lain.

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LIST OF SYMBOLS AND ABBREVIATIONS

LGG	-	Low Grade Glioma.
HGG	-	High Grade Glioma
CNN	-	Convolution Neural Network
FFBNN	-	Feed Forward Back Neural Network.
SVM	-	Support Vector Machine
DWT	-	Discrete Wavelet Transformer
FCM	-	Fuzzy C-Means
TI	-	Spin – Lattice
T2	-	Spin – Spin
WM	-	White Matter
GM	-	Gray Matter
SCF	-	Cerebro Spinal Fluid
FLAIR	-	Fluid-Attenuated Inversion Recovery
ROI	-	Region of Interest
RPN	-	Region Proposal Network
PD	-	Proton Density
DSC	-	Differential Scanning Calorimetry
MRI	-	Magnetic Resonance Image
CT	-	Computed Tomography
SC	-	Soft Computing
WHO	-	World Health Organization
PET	-	Positron Emission Tomography
SPECT	-	Single Photon Emission Computed Tomography
EEG	-	Electro Encephala Graph
NMS	-	Non Maximum Suppression
HU_A	-	Hidden units
Y_N	-	Desired outputs

Z_N	-	Actual outputs
RELU	-	Rectified Linear Unit
LF	-	Loss Function
RP	-	Right Positive
WP	-	Wrong Positive
RN	-	Right Negative
WN	-	Wrong Negative
ANN	-	Artificial Neural Network
BP	-	Back Propagation
QR	-	Quality Rate
GBM	-	Glioblastoma
ET	-	Enhanced Tumor
ED	-	Edema
NET	-	Non-Enhanced Tumor
NCR	-	Initial Weight Selection
AT	-	Active Tumor
E2E	-	End to End Train
MSE	-	Mean Squared Error
PSNR	-	Peak Signal to Noise Ratio
SOM	-	Self-organizing map
PCA	-	Principle Component Analysis
DT	-	Decision Tree

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CHAPTER 1

INTRODUCTION

1.1 Introduction and Research Backgrounds

Image segmentation is the route of dividing a digital image into various segments. The objective of segmentation is to make simpler and/or modification the illustration of an image into something that is more important and at ease to evaluate. Edge is one of the prime features of image. It helps us to analyze, infer and take decision in various image processing applications. This system proposes a supervised variation level set segmentation model in this project. Anomalous progression of tissue in an intensified manner within a living organism accounts for tumor. The cells existing within the tissue of a malignant tumor is responsible for self-multiplying itself and replicate all over feasible regions of a human physique. Tumor existing at varied stage causes a diversified effect in the human body.

Tumor cells usually demolish the well-being nature of a normal tissue by means of creating diverse symptoms like inflammation in the affected portion or to generate an added pressure in other organs of physique consequently causing a surge of pressure within the infected portion of the tumor [1]. In particular, a brain tumor prevailing in the stage of a metastatic level is designated as cancer that is traversed from other organs to the brain. During its preliminary stages, the transferring nature of a tumor that resembles a simple communicable disease is actually terminal (if not recognized). Hence, a better brain tumor processing methodology is a prerequisite of the present scenario. In general, images acquired through Magnetic Resonance (MR) are utilized for identification of brain tumor. In order to construct a perfect and robust brain tumor segmenting procedure, the faults surviving in the pre-existing techniques are assessed in this chapter for suggesting further improvisations in the methodology that is to be proposed in this research.

1.2 Existing System

In existing system, the system used Region based segmentation method. This method has two process. There are Region growing process and Region split & Merge process. In region growing process, the method has used to compare the candidate pixel and neighbor pixel. In region split & merge process, the process has used to identify the segment part.

Disadvantages:

- It does not identify the segment part effectively.
- It has high circuit complexity.
- It has high power consumption
- Low accuracy.

1.3 Proposed System

In proposed system proposes the statistical inference and global spatial properties. It would improve the segmentation of ROI(s) with heterogeneity and blurred boundaries in medical images. The system considers an image in a continuous domain to be partitioned into two segments: the foreground and the background.

Advantages:

- It is more effective to identify the segment part.
- It has no circuit complexity.
- Power consumption is very low.

1.4 The Statement of the Research Problem

The limitations of similar works in literature can be identified as: segmenting techniques of human brain tissue are mainly based on region growing and splitting and these techniques are not accurate enough. This can be explained as the edge between the different brain tissues are not been smoothen enough and the straight use of the averaging and median filters without proper preprocessing is contributing worse to the accuracy of the tissue detection. Therefore, there is a need for techniques before the segmentation that consider the edge sensitivity between the boundaries of different tissue and preserve these edge for better segmentation and classification of the human brain tissues.

1.5 The Research Objectives

The main research objectives of the proposed solution in this work can be listed as the following:

(i) To segmented the MRI image of brain tissues (healthy tissues, affected Edema tissues and tumor tissue) by using Faster R CNN,

(ii) To classify the glioma tumor of human brain tissues as (benign or malignant) by using two techniques (2D CNN and FFBNN) methods and

(iii) To evaluate the system in terms of the accuracy, MSE, PSNR, sensitivity, specificity and F1-score of segmentation and classification of the tissue for the purposes of more accurate medical diagnoses.

1.6 Proposed Methodology

The main processes of the proposed solution can be illustrated as in the Fig 1.1

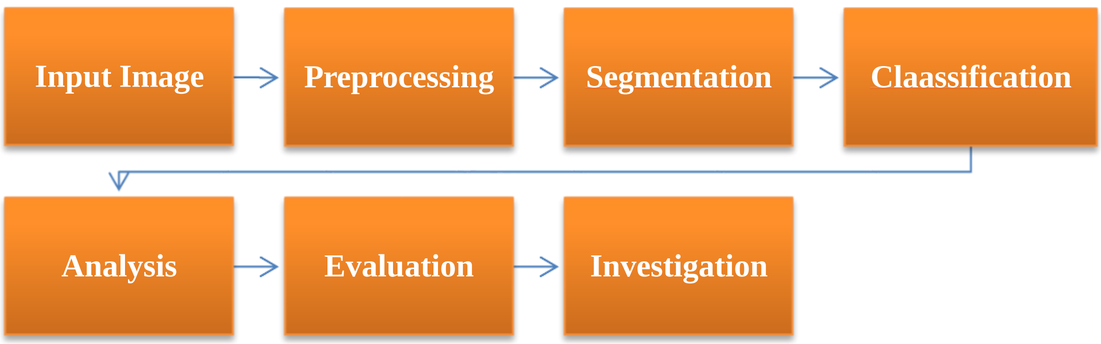

Figure 1.1 Proposed Methodology

The main Modules of this proposed work can be listed as:

1. Pre-Processing
2. Segmentation
3. Classification
4. Analysis
5. Evaluation
6. Investigation

1.7 Scope of Work

The First stage browses the given input image from the dataset and the second stage is Image preprocessing, also called image repair, involves the correction of distortion, degradation, and noise introduced during the imaging process. This process produces a corrected and enhanced image.

The third stage is Segmentation, Image division, additionally called marking, is the way toward separating the individual components of a picture or volume into a lot of gatherings, with the goal that all components in a gathering have a typical property. In the restorative area, this basic property is typically that components have a place with a similar tissue type or organ. Division of anatomical structures is a key empowering innovation for medicinal applications, for example, diagnostics, arranging and direction.

Restorative pictures contain a ton of data [2], and frequently just a couple of structures are intrigue. Division permits perception of the structures of enthusiasm, evacuating superfluous data.

The fourth stage is Classification: The Classification is to classify categories each alone based on the feature extracted values were extracted from segmented image as input [3] .Then compare the new input with data set were given before, the classification process depends on more parameters such as (mean, standard deviation, etc.).The result of classification is very important because its detect the type of tissues if it was (normal or abnormal), such as tumor, edema, healthy tissue and type of tumor.

The fifth stage is Analysis: system can do segmentation for regions of interesting in MRI and CT by using the algorithms. All segmentation methods require setup. The variation of initializations may lead to difference between the segmentation results to evaluate the hardness and reliability of the segmentation methods, for our dataset. The proposed system has to provide more data to training our algorithm and compare the segmentation results with different algorithms by compare the values of DSC [4], mean and standard deviation.

The sixth stage is Evaluation: Evaluate the performance of each method that has been used to segment the MRI image and classified the brain tissue and it can identify the advantages and disadvantages of each algorithm [5]. The Evaluation depends on many parameter or limitation to evaluate which one is the best such as (accuracy, sensitivity, specificity, etc.), and the seventh stage is investigation: the main purpose of this project is the Investigation to investigate if our system is useful and more accurate than other systems or algorithms the Investigation based on the evaluation process

1.8 Overview of Thesis Arrangement

This report consists of five chapters in total. Chapter one is Introduction chapter, chapter two is Literature Review, chapter three is Methodology, chapter four is Results and Discussions and chapter five is Conclusion as well as Recommendations.

Chapter one presents the idea of the research. This chapter reviews the image processing method and show the outcomes needed at the end of the research. The chapter also presents the objectives, problem statements and most importantly the scope of the research.

Chapter two reviews the theories and related researches. This chapter also explain in detail how the image processing works, the neural network, segmentations and what are the parameters that the image processing is looking for. By knowing the exact parameters, it can help the research goes in correct direction and understand the whole neural network used in the image processing.

Chapter three shows step by step of doing the research. This chapter will present the flow chart of algorithm to compute and improve the image. The chapter also presents how to use the PYTHON coding to model neural network as well as the segmentations.

Chapter four presents the simulation results. The results produced by the PYTHON will be explained mathematically or explain the results in the form of graphs.

Chapter five conclude the works or research and states some of the important statements to improve the research in future.

CHAPTER 2

LITERATURE REVIEWS

2.1 Introduction

Image processing is very important to get the image clear, zoom into enlarge the picture and eliminate the noise contents in the image. This section will present the theory about the segmentation of image and then reviews some of the image processing method using neural network. The neural network becoming more and more popular nowadays, even in the image processing.

Apart from reviewing the image segmentations and neural network, reviewing the published papers also important. Some of the published papers are similar to this research. By looking into those papers and compare the research, the gaps of the research can be find out. Data extraction techniques from Brain MRI image that can diagnose brain tumor and other diseases by the classification method.

In this section the proposed system mentions some segmentation and classification algorithms to extraction the data to diagnosis of brain tumor such as: Decision Tree (DT), Support Vector Machine (SVM), Fuzzy C-Means (FCM), Artificial Neural Network (ANN) and, K means cluster. The analysis it is very hard to tag a single data extraction algorithm as the best fit for the brain tumor detection or classification. consider segmentation of brain tumor is one of the complicated operations in medical field because the scene of the edema district is considerably to pinpoint. The force of the tumors diverges in every patient which makes the strict margin scene of the wounds to seem blurred in the MRI images. This section present also affords a serious costing of the texts studied, which tells new aspects of brain tumor segmentation [6].

The diagnosis by computer can improve and increase the diagnostic skills of physicians as a little time as possible with greater accuracy of diagnosis. The aim of this part is to survey the all issued of segmentation and classification techniques of the human brain. By using magnetic resonance images (MRI), to slice inputs into normal or abnormal by mixture attitude such as Faster R Convolution neural network for image segmentation and artificial neural network (CNN-ANN) method (research topic), in our research system proposed have proven the mixture attitude is perfect and fast and forceful [7].

There are more technics of scan like MRI scan, CT scan and PET scan for diagnosis, but MRI scan consider the best one because it is not upset the human body and it does not habit any radioactivity. There are more types of method were developed for brain tumor detection. In this project, two procedures are used for segmentation and classification, to delivers the perfect result for tumor and its grade. The tumor is abnormal decay of the tissues in any portion of the body. The tumor may be two level primary (low grade) or secondary (high grade). If it's a foundation, then it's known as primary. If the part of the tumor is supper to another apartment and grown up as its own, then it's known as secondary.

In general, the tumor in brain causes for strokes. The doctors treat the strokes but not treats the tumors. Therefore, the diagnosis of tumors is very significant for treatment. So the lifespan of the patients by the brain tumor can be rise if it's diagnosed detected at primary stage and may be save the patient's life or will increase the lifespan about 1 to 2 years [8].

2.2 Surgery Types of Tumor

In medical imaging, segmentation of images is very important in stages before surgery to remove the tumor. Image segmentation aids in identification of brain infections like determining correct size and volume of detected slice and the classification helps to recognize the qualitative the tumor in images. Because of the multiple shapes and sizes of brain tumors, it is difficult to diagnose and identify tumors accurately. The growth of tumors abruptly and quickly causes defects in neighboring healthy tissues [9].

2.2.1 Tumor

The term tumor (neoplasm) is an abnormal growth of a certain tissue’s cells, but tumor not meaning cancer.

2.2.2 Types of Tumor

There are three types or forms of tumors:
(1) Low grade glioma (Benign)
(2) Medium grade glioma (Pre-Malignant)
(3) High grade glioma (Malignant) (cancer will solely be malignant)

Benign Tumor: it is doesn’t grow in a sudden way; it doesn’t influence its neighboring healthy tissues and also doesn’t spread to t another tissues.
Pre-Malignant Tumor: it is a medium stage, think about as a disease, if not early treated it may result in cancer.
Malignant Tumor: is a term that is usually used for the adjective of cancer [9], word of the word Malignancy (mal- = “bad” and ignis = “fire”) that getting worse with time and finally leads to death of a person

2.3 Brain Imaging Techniques

The benefit of brain imaging techniques is help doctors and researchers to observe activity or problems in the brain, without need neurosurgery. The brain is very complex organ because its tissues and cells are connected and intertwined with each other in complex way, so imaging methods are more useful than laboratory analyzes in brain study without surgical intervention [10].

2.3.1 Ct Scan

A CT filter represents registered tomography check. It's conjointly alluded to as a CAT omputer Axial Tomography examines.It'sa therapeutic'imagingapproach that utilizes tomography.Tomography is the technique for producing a two-dimensional picture of a cut or segment through a 3-dimensional article (a tomogram). Enthusiasm for processed tomography originates from the way that, it's generally' open and offers high spatial goals pictures with quick securing modes: a cut can be gained in under a second, with normal spatial goals of in regards to 1 mm. Most CT gear comprises of a x-beam tube and an exact number of recognizing parts turning together around the patient

2.3.2 MRI

MRI give higher contrast for the variant brain tissues. MRI is more active for brain tumor detection and identification application, because the high contrast of soft tissues, and has high spatial resolution and is a non-invasive technique [11] and not based on the radiation. MRI images summarize important information for tissue parameters proton density (PD) and spin – lattice (T1) and spin – spin (T2) relaxation times, flow velocity and chemical shift), which afford more specific 'accurate brain tissue, so we preferring MRI as the method of choice in brain tumor studies.

2.4 Methods of MRI Images Segmentations

In this study, it makes a survey on the segmentation techniques used for brain images. In this part it compares our approach with a number of the published segmentation techniques where some hybrid techniques are used and others are the modified version of its basic. Table 2.1 shows a comparison between more than 30 segmentation algorithms for brain imaging techniques. Fig. 2.5 summarizes the segmentation techniques. Also, in order to compare various segmentation techniques [12], [13], summarizes, advantages and disadvantages of the used methods in brain tumor detection are discuss in detail.

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